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We have benefited from comments by Randy Becker and Jack Triplett, but all errors are of course the authors' own.

ABSTRACT

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Researchers in a large empirical literature find significant relationships between computers and labor productivity, but the estimated size of that relationship varies considerably. In this paper, we estimate the impact of computers and particularly of computer networks on plant-level productivity in U.S. manufacturing. Using new data on computer investment, we develop a proxy measure of computer inputs. We also develop a proxy measure of the plant's total capital stock from its book value, and clarify the conditions under which it is likely to be a good proxy for capital inputs. We find that computer networks and computer inputs have separate, positive, and significant relationships to U.S. manufacturing plant-level productivity.

I. Introduction

Researchers in a large empirical literature find significant relationships between computers and labor productivity, but the estimated size of that relationship varies considerably. Stiroh (2002) reviews twenty recent empirical studies, conducts a meta-analysis to assess the sources of differences in their findings, and concludes that the divergence of estimates likely reflects differences among the studies themselves in model specification and econometric techniques. Moreover, the way computers make their impact is not well understood.

In this paper, we estimate the impact of computers and particularly of computer networks on plant-level productivity in U.S. manufacturing. In our previous research (Atrostic and Nguyen 2002), we used the first survey data on the presence of computer networks in manufacturing plants, collected in the 1999 Computer Network Use Survey (CNUS), and found a positive and significant relationship between computer networks and productivity, controlling for other inputs to production, plant characteristics, and endogeneity of computer networks. However, the survey on computer networks did not collect information on the capital stocks of computers in these plants. Measures of networks, when not used together with measures of computer inputs, may simply pick up the presence of computers or the intensity of computer use. The findings from our previous research may, therefore, be subject to omitted variable bias.

In this paper, we link together plant-level data on the presence of computer networks from 1999 CNUS, computer investment from the 2000 Annual Survey of Manufactures (ASM), and book value of the plant’s capital stock from the 1997 Census of Manufactures (CM). Using the linked data, we develop a proxy measure of computer inputs from the plant’s computer investment and a proxy measure of the plant’s total capital stock from its book value, and clarify the conditions under which these measures are likely to be good proxies for capital inputs. We find that computer networks and computer inputs have separate, positive, and significant relationships to U.S. manufacturing plant-level productivity.

II. Computers, Computer Networks, and Productivity: Measurement Issues

Estimating plant-level relationships among computers, computer networks, and productivity requires overcoming many empirical challenges. Researchers must address the substantial standard measurement issues that arise in using plant-level data (see Griliches 1994 and Griliches and Mairesse 1995). Specific to the quest to understand the economic role of computers, electronic devices, and computer networks are yet more data gaps, including measures of computers and related information technologies, and computer networks (see, for example, Stiroh 2002; Haltiwanger and Jarmin 2001; Atrostic, Gates, and Jarmin 2000). The resulting empirical literature on computers and productivity is plagued with measurement issues that likely contribute to its divergent findings (Stiroh 2002). In this section, we focus on three specific issues, measuring capital inputs in general, measuring computer capital inputs, and estimating the effect of computer networks on productivity.

A. Measuring Capital Input

Our model requires measures of capital inputs or capital services. We want to control in our estimates for the plant's total stock of physical capital. For capital in general, measures of service flows can be generated from information on the capital stock, usually built up from data on capital investments using the perpetual inventory method. For time series analysis of plant-level data, one important problem is that assets are valued at their purchase price in book values, regardless of the timing of that purchase. In principle, adjustments to the book values of capital stock for plants that are not new in the current year could bring these values closer to measures of the plant's capital stock.[1] Adjustments based on book values and capital expenditures are made harder by data gaps for recent years. Book values are now collected less frequently in U.S. manufacturing, and for a smaller group of plants, than in the past. Book values of physical

[1] For example, Baily, Hulten and Campbell (1992) construct capital input measures based on perpetual inventory methods. Despite the potentially large empirical gap between book values and service flows measures, they find that both measures lead to similar empirical results for topics such as productivity dispersion. Stiroh (2002), in a more recent analysis, also finds little empirical difference. Other researchers (e.g.,Dunne *et al.* 2000; and Doms, Dunne, and Troske 1997), therefore, often use capital measures based on book values, whose homely virtue is that they are available.

capital (buildings and machinery) were collected annually in the CM and ASM until 1986. Since then, these data are collected only in the ASM in the Economic Census years (e.g., 1987, 1992, and 1997), and so are not even available for all plants covered by the economic census.

We avoid these problems in time-series analyses by using cross-section data. Many cross-section studies use the book values of the plant's total capital stock directly as a proxy for service flows (e.g., McGuckin *et al.*, 1998 and Greenan, Mairesse, and Topiol-Bensaid 2001). However, the book values that were collected in the ASM for 1997 included not just new plants, but all plants in the ASM, where the average age is roughly 10 years. We avoid this problem by limiting our sample to plants that are newly opened in 1997. Because these plants are new, we can assume that the book value equals the value of their stock of capital.

B. Measuring Computer Input

Similar to conventional (physical) capital, computers should be treated as a separate capital input in production and productivity analysis (e.g., Jorgenson and Stiroh 2000, Oliner and Sichel 2001). Computer services are the theoretically appropriate measure of computer input. Measures approximating this service flow must be constructed. For buildings and structures, and for machinery and equipment, proxies for service flows can be constructed from the book values collected for these forms of capital. However, a different approach is required for computer capital because its book value is not collected separately.

Computer service flows are normally estimated from measures of the computer capital stock in aggregate and industry-level productivity studies [e.g., Jorgenson, Ho, and Stiroh 2002; Triplett and Bosworth 2002). Studies using plant-level data often approximate computer service flows with measures of computer investment. Computer investment per worker is used as a proxy for computer input per worker in the plant in Berman, Bound, and Griliches (1994). It has been used as a measure of the presence of computers, or of computer intensity, or as a measure of the intensity of technology use in many recent studies. For example, Doms, Dunne, and Troske (1997) control for computer investment in their analysis of how adopting various technologies affects a series of plant-level economic outcomes. The multi-faceted analysis in Dunne *et al.* (2000) examines the role of computer investment in the dispersion of productivity and wages in U.S. manufacturing. Haltiwanger, Jarmin, and Schank (2003) use computer investment as a factor separate from total equipment investment in estimating productivity.

Using a plant's computer investment as a proxy for computer service flows requires the assumption that this investment is proportional to its stock of computer capital. This assumption allows researchers to use the only measure at hand. However, it may not be correct. Total plant-level investment typically is lumpy, while service flows are not. For example, Cooper, Haltiwanger, and Power (1999) find that plant-level investment surges are followed by periods of low investment. On the other hand, computer investment may be less lumpy than other investment if co-invention (investment in developing and implementing software that engages and connects computers and adapts them to plant-specific uses, e.g., Bresnahan and Greenstein 1997) continues in periods when there is no investment in computer hardware and software. Because the scale of co-invention over the life of the computer asset can be as much as the original computer investment (Bresnahan and Greenstein 1997), it is not clear whether the joint effect is to smooth or exacerbate lumpiness. However, any effect of co-invention on actual computer investment will not be captured in our measure because only data for investments in computer hardware and peripherals are collected in the 2000 ASM.

Finally, computer investment is collected occasionally, and in recent years was not collected at the same time as book values of capital. Computer investment data was collected in the CM for 1977 through 1992, but was not collected in 1997, and was only collected again in the ASM in 2000 and 2001.

C. Developing a Sample with Good Proxies for Computer and Capital Inputs

Starting from the sample of plants for which we have information on their use of computer networks, computer investment, and book values of total capital, we develop a sample for which our measures of computer and total capital are likely to be good proxies for computer and total capital inputs. Based on the insight that book value more closely measures capital service flows for new plants, we create a sample of plants that are new in the 1997 CM.

We define a sample of plants that first appeared in the 1997 CM because that allows us to assume that the book values of capital reported in 1997 are equal to the value of the plant's capital stock. That is, when a plant is new in 1997, $K_{T1997} \equiv BV_{T1997,}$ where K is the value of the plant's capital stock, T indexes total capital, and BV is book value. We first link all observations that have both information on computer networks in the 1999 CNUS and information on computer investment in the 2000 ASM. Because the 1999 CNUS and 2000 ASM samples each are drawn from a sample frame based on the 1997 CM, the probability-proportionate-to-size sampling strategy leads to a high overlap between the two samples, and the 1999 – 2000 linking rate is high.[2] Roughly one-third of the linked plants report positive computer investment. This response pattern is consistent the historical pattern when this item was collected in 1977, 1982, 1987, and 1992 (e.g., Dunne *et al*. 2000). We exclude plants that either do not report computer investment or report an amount of zero.[3] This means that the plants in our sample all have positive computer investment. We select plants in the linked sample and check that they first appeared in the 1997 CM (that is, they did not appear in the 1992 CM or the 1993 through 1996 ASMs).

We make the standard assumption that capital services are proportional to the value of the capital stock, so we can use the book values of total capital these plants report in the 1997 CM as a proxy for their total capital services in 2000, $S(K_{T2000})$.

(1) $S(K_{T2000}) \approx \pi \cdot BV_{T1997} \cdot \delta_{1.}$

The proportionality factor, π, represents services per unit of capital. The approximation error, δ_1, increases as 1997 differs from the year when the plant was new. That is, $\delta_{1\tau} \succ \delta_{1\upsilon}$ when $(1997 - \tau) \succ (1997 - \upsilon)$, for plants new in year τ compared to year υ. The approximation error encompasses the decline in efficiency as the 1997 capital stock ages, because it yields fewer capital services that it did when new.

We use the computer investment of these plants in 2000 as a proxy for their computer capital stock in 2000. That is, we assume

(2) $K_{c2000} \approx \delta_2 \cdot I_{c2000}$,

where K_{c2000} represents the plant's actual computer capital stock; δ_2 is a constant, assumed to be the same among these plants because they opened in the same year, 1997; and I_{c2000} is the plant's computer investment in 2000.

This sample definition yields 849 observations containing the information we need to create measures of computer networks, computer and total capital, and other inputs. It is conceptually the best sample that the data will allow us to create. We address the concern that

[2] Haltiwanger, Jarmin, and Schank (2003) find little sample reduction when they link the 1999 CNUS and the 2000 ASM. Their final sizes are range from 22,700 to 22,900, depending on specification.
[3] The data as entered in the CES data storage system do not allow us to distinguish between plants that do not report computer investment and those that report zero, so we exclude both.

the sample is small by constructing a second sample based on a broader alternative definition of new that includes plants between three and eight years old. The broader definition includes plants that first appeared in the 1993 through 1996 ASMs and have positive computer investment. These plants are between three and eight years old in 2000, below the 10-year average age of plants in the 1999 CNUS – 2000 ASM linked data set.[4] The value of the total capital approximation error, δ_1, will be higher for these plants than for plants that are new in 1997, but including them yields a larger sample of 1,755 observations.

To test the importance of using the sample of plants for which book values are a good proxy for the capital stock, we use the linked data to construct a data set containing plants of all ages. Our sample of plants of all ages that report positive computer investment has 12,386 observations.

D. Estimating the Impact of Computer Networks

We want to estimate the impact of computer networks because they may be a new technology that shifts the production function. Simply using computers seems unlikely to be such a shift, since computers have been in commercial use in the U.S. for fifty years, and they might be viewed as just another capital input. Computer networks also have been in used for decades. But the networks that came into use more recently are thought to be qualitatively different (e.g., Bresnahan and Greenstein 1997). Brynjolfsson and Hit (2000) argue that the effects of organizational changes caused by the newer computer networks may rival the effects of changes in the production process. Viewed this way, computer networks are a productivity-enhancing general-purpose technology (Breshnahan and Trajtenberg 1995). The question for productivity and other measures of economic performance may no longer be whether computers matter, but whether it matters how computers are used.

Despite the importance of understanding whether computer networks matter for productivity, information on networks is scarce. The computer network information collected in the 1999 CNUS is the first such collection for a large and representative national sample of plants in U.S. manufacturing. But because these data are new, we also want to be sure that they

[4] Haltiwanger, Jarmin, and Schank (2003).

actually measure something distinct from computer inputs. The information on the presence of computer networks of course is but one indicator of how plants use computers. However, it also is a relatively simple and clear one. It is worth determining whether a measure of the presence of computer networks has empirical value because relatively little information needs to be collected to construct it.[5] If this measure alone can convey important additional information about firm heterogeneity in the uses of computers, and in particular on the newest uses, there is an argument to be made for considering eking out room for its components in survey instruments and respondent burden calculations.

We want to see whether both computers and networks have a statistically significant relationship to productivity. Because a standard empirical finding in plant-level cross-section estimates is that the omitted variables problem may be serious, estimates of the impact of computer networks need to take account of the plant's computer inputs.

The 1999 CNUS network data, together with the computer investment information collected in the 2000 ASM, allow us for the first time to specify an empirical model of labor productivity with separate measures of computer inputs and computer networks. We use information collected in the 1999 CNUS to create a computer network dummy variable that takes on a value of one if the plant reports having a computer network, and zero otherwise. Networks can be of several kinds, including Electronic Data Interchange and the Internet, and plants can have multiple kinds of networks.

III. Empirical Implementation

In our empirical work, we use the three samples described in the preceding section. The primary data set in our analysis consists of the 849 manufacturing plants that have computers, are new in 1997, and for which we have computer investment and network information. To test the robustness of the empirical results to alternative cohort definitions that the data allow us to

[5] The 1999 CNUS did not ask a single question about whether a plant had a network. It asked the plant to check whether it used each of several kinds of networks (e.g., Internet, Electronic Data Interchange). Plants can use more than one kind of network. We construct our network measure from those separate responses.

construct, we use the sample of 1,755 plants that are new since 1992 and have computer investment. We also use the data set of 12,386 plants of all ages that have computer investment. It allows us to assess the empirical importance of using book values as proxies for capital services when they are unlikely to be good measures. Because information on computer networks was collected only in 1999, our analyses are all cross-sectional.

A. Equation Specification

To assess the relationship between computer networks and computer input on plants' labor productivity, we estimate the following equation:

$$\text{(3)} \quad \mathrm{Log}(Q/L) = \beta_0 + \beta_1 \mathrm{CNET} + \alpha_{1c}\log(K_c/L) + \alpha_{1nc}\log(K_{nc}/L) + \alpha_2\log(M/L)$$
$$+ \alpha_3\log(\mathrm{MIX}) + \alpha_4 \mathrm{MULTI} + \sum\gamma_j \mathrm{SIZE}_j + \sum\lambda_i \mathrm{IND}_i + \varepsilon$$

where Q, K_c, K_{nc}, L, and M represent output, computer capital input, non-computer capital input, labor, and materials. CNET denotes computer networks. SIZE denotes the size class of the plant. MIX denotes the mix of production and non-production workers, and MULTI represents plants that belong to a multi-unit firm. IND denotes three-digit NAICS industries.

Our model distinguishes between the productive effect of computer input in the plant, and a technological shift resulting from using computer networks. Equation (3) directly relates computer networks and computer capital to (log) labor productivity. In this formulation, β_1 is one of our two parameters of interest. It can be interpreted as measuring the effect of computer networks on labor productivity, controlling for the intensities of computer and non-computer capital (K_c/L and K_{nc}/L), and materials intensity (M/L).

The second parameter of interest is α_{1c}, the coefficient on the intensity of computer capital. This coefficient can be interpreted a measure of the flow of services from the stock of computer capital, controlling for the presence of computer networks and other inputs. Our model differs from those in most previous related plant-level studies in that ours is a three-factor production function in which output is defined as gross output (rather than value added) and materials are incorporated as a separate input in production.

In this paper, we focus on estimating whether labor productivity is related both to computer networks and computer inputs. Labor productivity is defined as output per worker, (Q/L). We use total value of shipments (TVS) as a measure of Q. Our measure of labor, L, is the total number of employees in the plant. We described earlier how we use the CNUS, ASM, and CM to specify computer networks, computer inputs, and total capital inputs. Our empirical specification in equation (3) uses the intensities of computer and capital input. Computer investment divided by employment, and book value of capital divided by employment, are the variables included in the reported estimations. To estimate the specification in equation (3), we also need information on other inputs and plant characteristics. We use the same empirical specifications of materials, skill mix, size, multi-unit plant status, and industry as Atrostic and Nguyen (2002), and describe them in the Appendix.

B. Data

The CNUS data we use in this study are part of a Census Bureau measurement initiative to fill some of those data gaps on the growing use of electronic devices and networks in the economy (Mesenbourg 2001). The appendix contains more information on the 1999 CNUS, 2000 ASM, and the 1992 and 1997 CM.

IV. Empirical Findings

We estimate three alternative specifications of labor productivity. The preferred specification includes both computer networks and computer inputs. A specification that parallels our prior research includes computer networks but not computer inputs. The third specification parallels specifications in the literature that include computer inputs but not computer networks. We estimate these specifications for the cohort of 849 plants that newly opened their operations in 1997 and had positive computer investment in 2000, and report the results in Table 1. To show whether it matters that we restrict our sample to plants that were new in 1997 (because 1997 book value should correctly measure their total capital stock), we estimate the same three specifications using two other samples. Estimates from the sample of 1,755 relatively new plants that opened between 1993 and 1997 and have positive computer investment in 2000 are reported in Table 2. Estimates from the sample of 12,836 plants of all ages that have positive computer investment in 2000 are also reported in Table 2.

Computer investment and computer networks both have positive and significant relationships to labor productivity in estimates from our preferred specification, as reported in column (1) of Table 1. The coefficient on computer networks is 0.117, controlling for computer and other inputs and plant characteristics.[6] Computer investment has a separate and significant effect, with a coefficient of computer intensity (K_c/L) of 0.050. Computer networks are significant when they enter the estimation alone, and the coefficient of 0.136, reported in column (2), is higher than when computer investment is included. When computer networks are excluded and computer investment is included alone, computer intensity is significant, with the slightly higher coefficient of 0.052 as shown in column (3) of Table 1.[7] These estimates show that it matters empirically whether data are available to measure both computer networks and computer inputs. Coefficients of both computer measures are significant. However, each coefficient also is higher in the specification that excludes the other measure, suggesting that when each is used alone, it picks up part of the impact of the other.

The coefficient of one other variable, MIX, the ratio of non-production to production workers, changes appreciably across these specifications. In our preferred specification that includes both computer investment and networks (column (1) of Table 1), the coefficient of MIX is 0.040, but is not significant. An estimate similar in size, 0.044, and in lack of significance, comes from the specification that includes only computer investment (column (3)). By comparison, in the specification that only includes computer networks, the coefficient of MIX increases to 0.061, suggesting that computer inputs may be positively related to the worker mix ratio (column (3)). Coefficients of most other inputs, plant characteristics, and R^2, change little across the three specifications reported in Table 1, suggesting that the computer network and computer input measures are not related to other inputs or plant characteristics.

We next assess whether these estimates are sensitive to the assumption that book value best measures capital inputs for new plants by estimating the same three specifications for the samples of plants that are newly opened between 1992 through 1997. We create four separate samples for plants that have computer investment and are new in each year between 1993 and 1997, and also combine them into a fifth sample of all plants that are new between 1992 and

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[6] More precisely, the exponential of the coefficient 0.117 is 1.124, or a differential of 12.4 percent. However, because the differences between the exponential and the coefficient are not large, we discuss the coefficient rather than the exponential in the text.
[7] While we calculate coefficients for industry dummies λ, and for size dummies γ, we do not report them because such coefficients present standard micro data disclosure problems.

1997. Because the empirical findings are qualitatively the same, we report in Table 2 the findings for the largest sample size, the 1,755 plants that are new between 1992 and 1997.

The empirical findings using this broader definition of "new" plant are similar to those for plants that are new in 1997. Computer investment and computer networks both have positive and significant relationships to labor productivity, as reported in column (1) of Table 2. The computer network coefficient of 0.126 is significant for relatively new plants with computers, controlling for computer and other inputs and plant characteristics. Computer investment has a separate and significant effect, with a coefficient of computer intensity (K_c/L) of 0.046. When computer networks are excluded, computer intensity remains significant, with a slightly higher coefficient of 0.049, as shown in column (2) of Table 1. When computer inputs are excluded and computer networks are included alone, computer networks remain significant, with a higher coefficient of 0.1510.

Estimates based on our sample of plants of all ages show the empirical importance of selecting samples for which book values of capital should be good proxies for capital services. Coefficients of both computer networks and computer input are significant in the estimates using samples based new plants, as reported in Tables 1 and 2. A very different picture emerges from estimates based on plants of all ages. In these estimates, computer networks do not have an effect on labor productivity separate from computer inputs. The network coefficient of 0.004, reported in column (4) of Table 2, is not statistically significant. Computer investment, however, is positively and significantly related to productivity, with a coefficient of 0.043.[8] Using this sample, computer networks do not appear to be a technology that shifts the production function, distinct from the productive effect of computer inputs. Instead, computer networks appear simply to be a measure of computer inputs. However, this also is the sample for which using book values of capital as proxies for capital inputs are most problematic.

[8] We report only OLS estimates. Because we use new, or relatively new, plants, we have no good instruments. The two-stage estimates reported in our prior research did not have the expected result of reducing the estimated effect of computer networks. When we estimate OLS on the same sample used to in the two-stage estimates, coefficients of variables other than networks and computer investment are stable.

V. Discussion

Our empirical findings suggest that using computer networks may be a new technology that shifts the production function and is separate from computer inputs. They also suggest that the measurement issues we raise about capital inputs have important empirical consequences, because those findings hold only when we have good proxies for capital inputs. When we do not have good proxies, we would conclude instead that our cross-section estimates of the separate effects computer networks and computer inputs are subject to omitted variable bias, and that the new network variable yields no additional information about the impact of computer use in U.S. manufacturing.

To assess these findings, we compare them with results we obtained in our previous study using these data, when only information on computer networks was available. We also compare our findings with those of other researchers. The final portion of this section discusses two aspects of data gaps: How remaining data gaps may affect our estimates, and what our findings imply for priorities in filling them.

A. Comparison with Prior Research Using These Data

Our findings in this paper are consistent with our previous research using these data that showed significant and positive impacts of computer networks on labor productivity in both OLS and two-stage regressions (Atrostic and Nguyen 2002). The appropriate comparison is with network coefficients reported in that study based OLS regressions on the 17,787 observations sample that we also used in the two-stage estimates. Those OLS estimates are repeated here in column (2) of Table 3. They show that labor productivity is 3.3 percent higher in plants with networks.[9]

The new estimates we report for the productivity impact of networks for plants are much higher than we found in our previous research. However, our previous and new estimates are not directly comparable because the samples differ in two ways. The sample we use in this paper is

[9] In contrast to standard findings in estimates from OLS vs. two-stage regressions, our previous research shows a positive and significant computer network effect in both, and the effect estimated in the two-stage regressions, 6.0 percent, exceeds the OLS estimate of 3.3 percent. We obtain the 6.0 percent estimate by evaluating the significant coefficient of the predicted network variable (0.505) at the mean of the network variable.

for plants that are new in 1997 and have computer investment. Our previous research includes plants of all ages, and, because data on computer investment were not available, did not use the presence of computer investment to define the sample. [10]

With those two differences in mind, we compare the specification that is most similar in the new and previous research. This specification includes networks but not computer inputs. The estimated network impact is 13.6 percent for plants new in 1997 (column (2) in Table 1). This is more than four times the 3.3 percent impact of networks in our previous research. The MIX coefficient also is higher for the new plants (0.061 vs. 0.039). This suggests that newer plants that are more productive have a higher proportion of non-production workers. The remaining coefficients are broadly similar across the several age-based samples reported in Tables 1, 2, and 3.

Our finding that computer networks have a higher productivity impact in newer plants might seem to lend some support to the vintage capital model, on which the existing empirical literature yields mixed findings (Bartlesman and Doms 2000).[11] However, what our research finds is that computer networks have a higher productivity *impact* in newer plants. Those new plants have lower average productivity, regardless of whether they have networks. Also, the new findings we report in this paper are for plants that had positive computer investment in 2000. Plants with computer investment may be better able to exploit network technology.

The MIX term, the ratio of non-production to production workers, is the other variable whose coefficient differs substantially between the new estimates in this paper and our previous research. Higher ratios of non-production to production workers are frequently taken as proxies for higher levels of skills embodied in the workers. Careful research linking the broad groupings

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[10] We also perform parallel sensitivity assessments between the 12,836-observation data set of plants of all ages that we use in this paper 17,787-observation 1999 CNUS-only data used in our previous research (Atrostic and Nguyen 2002). Because the same specification estimated on these two data sets yield similar results to those reported here, we do not discuss them separately.

[11] The vintage capital model says that newer plants open with the newest, embodied technology, and that plants exit when their productivity becomes too low relative to the new entrants. Consistent with the model are results in the literature suggesting that older plants are more likely to exit, but more productive plants are more likely to continue. However, Baily, Hulten, and Campbell (1992) find little evidence for the vintage capital model in examining transition matrices across years in U.S. manufacturing. They and other researchers find that plants entering an industry have low productivity on average, but move within a few years to both the highest and lowest productivity groups. Similarly, Power (1998) finds that productivity increases with plant age, but finds almost no relationship between productivity and the age of investments.

of production and non-production workers with reports from the 1990 Decennial Census of actual worker education suggests that there can be such embodiment (Doms, Dunne, Trostke 1997). However, we cannot make such linkages with our data. The broad worker classification in the MIX term makes it difficult to read too much into any estimated difference in this coefficient between groups of plants of different ages.

B. Comparisons with The Information Technology Literature

Our finding of positive and significant relationships between computers and computer networks and productivity is consistent with the recent empirical literature and the plant and firm level. Previous research using the computer investment data for U.S. manufacturing through 1992 found a positive link with plant-level productivity, with much variation among industries (Stolarick 1999 a and b). Two recent reviews of plant- or firm-level empirical studies of information technology (including but not limited to computers) and economic performance (Dedrick *et al.* 2003 and Stiroh 2002) conclude that the literature shows positive relationships between information technology and productivity.

Dedrick *et al.* (2003) review over 50 articles published between 1985 and 2002, many of which are firm-level studies with productivity as the performance measure. They conclude that firm-level studies show positive relationships, and that gross returns to information technology investments exceed returns to other investments.[12]

Stiroh (2002) conducts a meta-analysis of twenty recent empirical studies of the relationship between information technology and the production function. He also estimates a number of specifications used in those studies on a single industry-level database. The meta-analysis of 19 firm-level studies that use gross output productivity measures yields a mean elasticity of information technology of 0.042, with large variability around that coefficient. His estimates using the single industry-level database yield OLS estimates of computer capital

[12] They warn against concluding that higher gross returns mean that plants are under-investing in information technology. Most studies do not adjust for the high obsolescence rate of information technology capital, which lowers net returns. Also, total investment in information technology may be understated because most studies measure only computer hardware, but not related labor or software, or costs of co-invention, such as re-engineering business processes to take advantage of the new information technology.

elasticity of 0.047.[13] The coefficient estimate, however, is sensitive to econometric specifications that account, for example, for unobserved heterogeneity.

Stiroh's meta-analysis and basic OLS regression estimates are close to the coefficient of 0.050 that we report for computer capital elasticity in new plants, in our preferred specification in column (1) of Table 1. It is the same as the coefficient of 0.046 that we report in estimates based on our larger sample of plants that are new between 1993 and 1997.

While we are reassured by this empirical regularity, we do not make overly much of it. Our coefficient estimate, like most others, is not adjusted for the high obsolescence rate of computers. It also is subject to other biases whose net effects may be of any sign. There is a downwards bias because computer prices continue to fall sharply. The price ratio for computers between 1997 and 2000, Pc1997 / Pc2000, is certainly greater than one, and in fact is closer to three (a 30 percent annual rate of decline). The plant's computer investment in 2000 buys much more computer input than the same dollar investment would have bought in 1997, so we overstate the effective computer input. There is an upwards bias in our estimates, as in the estimates in Stiroh (2002), because we do not measure co-invention. Co-invention is estimated to equal roughly the cost of the hardware and peripheral equipment investment over the life of the investment, so omitting it understates computer inputs.

Our findings also are consistent with a relatively new literature in plant- or firm-level research conducted in other countries and summarized in Pilat (2003). Many studies cited there find positive relationships between information technology and productivity. Several of those studies also find positive relationships between using computer networks and productivity (e.g., Baldwin and Sabourin (2001) for Canada; Bartlesman *et al.* (1996) for the Netherlands, and Criscuolo and Waldron (2003) for the United Kingdom). A new paper by Motohashi (2003) finds separate positive effects of computer expenditures and computer networks in Japan between 1990 and 2001, with larger effects in more recent years, but also with much heterogeneity in those effects.

Stiroh (2002) concludes that information technology matters, but the wide variation in

[13] Both Dedrick (2003) and Stiroh (2002) attribute the failure of early micro data studies to find a relationship to inadequate data with small sample sizes.

empirical estimates means that much "depends on the details of the estimation" and "one must be careful about putting too much weight on any given estimates." We agree. Our results reported in this paper and the several specifications reported in our previous research show that theory, specification, and measurement issues matter. Our conclusions also are consistent with the empirical micro literature: computer inputs and computer networks are related to plant-level productivity.

C. Important Data Gaps and Implications for Data Collections

The new computer network and computer investment variables narrow important gaps in the data we need to understand how information technology affects plant-level productivity. The plant- or firm-level data needed to address the effect of computer networks seldom existed until very recently. These are among the important data gaps that were identified in reviews of the data needed to understand the emerging electronic economy, e.g., Atrostic, Gates, and Jarmin (2000), and Haltiwanger and Jarmin (1999), and that some recent data initiatives address (Mesenbourg 2001).

Early studies lacked large representative national samples collected by official statistical organizations. For example, Dedrick *et al.* report that Barua (1995) draws on 60 business units in 20 U.S. companies. Similarly, Brynjolfsson and Hitt (2000) and (2002) analyze between 500 and 600 firms for which they combine information from a private database on the firms' capital stock with public financial information from Compustat. Analyses by these and other early researchers used the best data then available, but were constrained by small sample sizes, few or no small firms or plants, and lack of data on information technology investment (see, for example, parallel discussions in Stiroh 2002 and Dedrick *et al.* 2003).

Larger samples of roughly 38,000 plants became available in the 1988 and 1993 Surveys of Manufacturing Technology (SMT) for the U.S., but were limited to five two-digit SIC industries. Also, while the SMT collected data on the use of a number of technologies, Doms, Dunne, and Troske (1997) stress that they are process and control technologies, and not measures based directly on the use of computers.

The network data in the 1999 CNUS and the 2000 ASM provide critical new data. However, they only provide it for one period. We have enough data to create instruments for the network variable and estimate a 2SLS productivity regression. Because the new network data were only collected once, in 1999, however, we cannot use panel data techniques to address many standard plant-level measurement issues, including unobserved heterogeneity beyond those input and plant characteristics we control for, such as managerial ability. Nor can we address sources of heterogeneity that are specific to studies of information technology and computers, such as reorganization of work processes, because such data are not collected in our sources. And long-standing data gaps, such as the absence of information on worker occupation and skills, mean that we cannot control for differences among plants in worker quality. Nor can we investigate how the presence of computers and computer networks affect the dynamics of plant performance.

A large literature lays out major data gaps in estimating the impact of information technology on economic performance, including Dedrick *et al.* (2003); Pilat (2003); Atrostic, Gates, and Jarmin (2000); and Haltiwanger and Jarmin (1999). Some of the largest data gaps affecting our analysis for the manufacturing sector will be addressed in the 2002 Economic Census. Data will be collected on both the book values of assets and capital expenditures, with separate information on expenditures on computer equipment and peripherals. In addition, beginning with data for 2003, the Annual Capital Expenditures Survey (ACES) will collect information on both capitalized and expensed expenditures on information and communications technology structures, and equipment, including computer software. However, ACES is collected at the company level, so neither totals nor separate detail for expenditures on these information technology expenditures will be available at the plant level.

VI. Conclusions

We use new data on computer networks and computer investment and find that both have positive and significant impacts on plant-level labor productivity in U.S. manufacturing. This finding suggests that computer networks are a new technology that shifts the production function, distinct from the productive effect of computer inputs in the production process. We also show the empirical importance of having good proxies not just for the computer network and computer inputs variables of interest, but also for total capital inputs. When we do not, we would conclude that, while computer networks may not be pencils, they are merely computers.

New data raise the level in the statistical glass, but also raise our expectations for the questions we can answer, without enabling us to address all them (Griliches 1994). The statistical glass nevertheless is filled higher for U.S. manufacturing than for other sectors. Data on variables critical to this analysis, such as computer networks, computer investment, book value of capital, and other inputs, such as materials, seldom exist in official U.S. data collections for sectors outside of manufacturing. The impact of computer inputs and computer networks remain hard to measure, and their measurement is important.

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Table 1. Labor Productivity OLS Regression Results: Plants New in 1997

Dependent Variable: Labor Productivity
(T-statistics in parentheses)

	Plants with Positive Computer Investment in 2000			
	New in 1997			**All Plants**
Independent Variables	**(1)**	**(2)**	**(3)**	**(4)**
Intercept	**3.769 (32.63)**	**3.051 (32.36)**	**3.266 (38.00)**	**2.949 (106.03)**
CNET	**.117 (2.12)**	**.136 (2.44)**	**(--)**	**.004 (0.25)**
Pr (CNET)	**(--)**	**(--)**	**(--)**	**(--)**
Log (K_{c2000}/L)	**.050 (4.36)**	**(---)**	**.052 (4.53)**	**.0478 (16.03)**
MIX	**.040 (1.69)**	**.061 (2.64)**	**.044 (1.85)**	**0.04 (7.08)**
Log (K/L97)	**.086 (6.02)**	**.093 (6.42)**	**.088 (6.13)**	**.098 (26.92)**
MULTI	**.161 4.81)**	**.155 (4.59)**	**.167 (5.00)**	**.102 (11.45)**
Log (M/L)	**.409 (28.00)**	**.422 (29.15)**	**.409 (27.96)**	**.478 (121.97)**
Plant Size	**Yes**	**Yes**	**Yes**	**Yes**
Industry (3-digit NAICS)	**Yes**	**Yes**	**Yes**	**Yes**
R^2	**.655**	**.647**	**.653**	**.740**
Number of Plants	**849**	**849**	**849**	**12,386**

Table 2. Labor Productivity OLS Regression Results:
Plants New Between 1992 and 1997

Dependent Variable: Labor Productivity
(T-statistics in parentheses)

	Plants with Positive Computer Investment in 2000			
	New between 1992 and 1997			**All Plants**
Independent Variables	**(1)**	**(2)**	**(3)**	**(4)**
Intercept	**3.009 (39.78)**	**2.916 (39.26)**	**3.117 (47.90)**	**2.949 (106.03)**
CNET	**.126 (2.78)**	**.1510 (3.31)**	**(--)**	**.004 (0.25)**
Pr (CNET)	**(--)**	**(--)**	**(--)**	**(--)**
Log (K_{c2000}/L)	**.046 (5.42)**	**(---)**	**.049 (5.71)**	**.0478 (16.03)**
MIX	**.036 (2.13)**	**.057 (3.51)**	**.038 (2.25)**	**0.04 (7.08)**
Log (K/L97)	**.084 (8.91)**	**.088 (9.28)**	**.085 (9.01)**	**.098 (26.92)**
MULTI	**.143 (5.71)**	**.137 (5.43)**	**.149 (5.98)**	**.102 (11.45)**
Log (M/L)	**.456 (43.38)**	**.466 (44.54)**	**.457 (43.34)**	**.478 (121.97)**
Plant Size	**Yes**	**Yes**	**Yes**	**Yes**
Industry (3-digit NAICS)	**Yes**	**Yes**	**Yes**	**Yes**
R^2	**.678**	**.672**	**.665**	**.740**
Number of Plants	**1,755**	**1,755**	**1,755**	**12,386**

Table 3. Labor Productivity Regression Results

Dependent Variable: Labor Productivity
(T-statistics in parentheses)

	All CNUS Plants[1]		
	All	With Positive 1992 Computer Investment	
	OLS	OLS	Two-stage
<u>Independent Variables</u>	(1)	(2)	(3)
Intercept	2.678 (159.95)	2.830 (119.48)	2.357 (32.50)
CNET	.046 (5.76)	.033 (3.00)	(--)
Pr (CNET)	(--)	(--)	.505[2] (6.41)
Log (K_{c2000}/L)	(--)	(--)	(--)
MIX	.043 (12.28)	.039 (8.40)	.037 (8.12)
Log (K/L97)	.091 (39.86)	.088 (28.81)	.084 (26.61)
MULTI	.114 (19.30)	.101 (12.58)	.039 (3.31)
Log (M/L)	.515 (206.74)	.505 (148.93)	.506 (150.48)
Plant Size	Yes	Yes	Yes
Industry (3-digit NAICS)	Yes	Yes	Yes
R^2	.756	.750	.756
Number of Plants	29,808	17,787[3]	17,787[3]

1 All coefficients are reported in Atrostic and Nguyen 2002

2 Evaluating the coefficient of the predicted probability at a point consistent with our data yields an estimated network effect of six percent. This estimated network effect is slightly higher than in the OLS estimates of column (2).

3 The number of observations in columns (2) and (3) is smaller than in column (1) for several reasons. Some plants present in the 1999 ASM did not exist in 1992. Plants in existence in 1992 may not have reported the information on the 1992 computer investment from the 1992 CM that is used to predict CNET in the two-stage estimates. The sample in column (2) is restricted to the sample in column (3).

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Appendix: Data and Empirical Specification of Variables

Data

The 1999 Annual Survey of Manufactures Computer Network Use Supplement was mailed to the plants in the ASM sample in mid-2000. The supplement asked about the presence of computer networks, and the kind of network (EDI, Internet, both). It also collected information about manufacturers' e-commerce activities and use of e-business processes. The questionnaire asked if the plant allowed online ordering and the percentage of total shipments that were ordered online. Information on online purchases was also asked. In addition, information was collected about the plant's current and planned use of about 25 business processes conducted over computer network (such as procurement, payroll, inventory, etc., "e-business processes") and the extent to which the plant shared information online with vendors, customers, and other plants within the company.

The Annual Survey of Manufactures (ASM) is designed to produce estimates for the manufacturing sector of the economy. The manufacturing universe consists of approximately 365,000 plants. Data are collected annually from a probability sample of approximately 50,000 of the 200,000 manufacturing plants with five or more employees. Data for the remaining 165,000 plants with fewer than five employees are imputed using information obtained from administrative sources. Approximately 83 percent of the plants responded to this supplement. All CNUS data are on the NAICS basis. Because the data are only from respondents to the CNUS, and are not weighted (see the discussion in www.census.gov/estats), our results may apply only to responding plants. We note, however, that the plants responding to the CNUS account for a substantial share of the U.S. manufacturing employment and output (about 50 to 60 percent) represented in the ASM.

Variables

- *Capital (K):* Data on capital services are the appropriate measure for production function estimation and productivity analysis. Because such data are not available at the micro level, we use book values of gross capital stocks (including buildings and machinery assets) collected in the 1997 CM as a proxy for K. We use 1997 data on capital intensity (K/L) because data on total capital stock are collected in the 1997 Economic Census but not in the ASM. Although we recognize that these data have limitations as measures of capital services, it is widely recognized that it is difficult to handle these problems in cross-sectional analysis. We therefore follow many previous studies (e.g., McGuckin *et al.*, 1998 and Greenan, Mairesse, and Topiol-Bensaid (2001)) and use book values of capital as a proxy for capital input, K. This implies that services are proportional to the book value of capital. This assumption is made more reasonable by the controls for plant characteristics in our regressions

- *Materials (M):* are the sum of values of materials and parts, values of energy consumed (including electricity and fuels) and values of contract work.
- *Skill Mix (MIX)*. This variable is defined as the number of non-production workers (OW) divided by total employment (TE) in the plant, as reported on the 1999 ASM. Computer networks require highly skilled workers to develop and maintain them. Productivity might thus be higher at plants with a higher proportion of skilled labor because these workers are able to develop, use, and maintain advanced technologies, including computer networks. But applications such as expert systems may allow a function to be carried out with employees who have lower skill levels, or with fewer employees.[14]

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[14] Occupational detail would be desirable to test the relationship among productivity, networks, and the presence of such skilled occupations as computer programmers and systems support staff (e.g., Greenan, Mairesse, and Topiol-Bensaid (2001) and Motohashi (2001)). However, the ASM only collects information on the total numbers of production and non-production workers in the plant, with no further detail by process, function, or worker characteristic. Dunne and Schmitz (1992) found that plants in the 1988 SMT that used advanced technologies had higher ratios of non-production to total workers. Doms, Dunne, and Troske (1997) find that plants that adopt new technologies have more skilled workforces both before and after adoption. As with many other plant-level studies, we use this employment ratio to proxy for skill mix in our productivity estimates. Production workers accounted for about one-quarter (27 percent) of employment among CNUS respondents in manufacturing. This share is similar to shares reported for the five two-digit U.S. Standard Industrial Classification (SIC) industries in the 1988 and 1993 SMTs (e.g., McGuckin *et al.* 1998).

However, some production workers are in highly skilled occupations, and some non-production workers are in relatively less skilled jobs such as janitors, and the literature is scarcely unanimous that the nonproduction labor share is a measure of skill (e.g., Dunne, Haltiwanger and Troske (1997) and Berman, Bound, and Griliches (1994). We follow Dunne *et al.* (2000) in both using this measure and being cautious in interpreting it as an indicator of skill.

• *SIZE*: Plant size is specified as a standard series of six dummy variables. About 30 percent of the plants in our core CNUS sample have fewer than 50 employees, 20 percent have between 50 and 99 employees, about 30 percent have between 100 and 250 employees, and the remaining 20 percent are in larger plants.

• *Multi-unit firms' plants (MULTI)*: Many manufacturing plants are part of multi-unit firms, so employment size alone is an inadequate indicator of available resources, managerial expertise, and scale. We construct a dummy variable, "MULTI," that takes on the value of one if the plant is part of a multi-unit firm, and equals zero otherwise. Nearly two-thirds of the plants in our sample are part of a multi-unit firm.

• *Industries* (*IND)* : All previous studies of plant-level behavior note substantial heterogeneity among plants within detailed manufacturing industries, as well as between detailed industries. There are 21 3-digit NAICS manufacturing industry groups in our sample (NAICS codes 311- 316, 321- 327 and 331-337). Industry dummies ("IND") are included in the basic empirical model specifications to capture industry-specific effects on plant-level labor productivity.